Education Working Paper Archive

Does Competition in schools increase grade inflation?

January 15, 2010

Patrick Walsh

St. Michael's College

Does competition among schools encourage grade inflation?

Patrick Walsh

Department of Economics, St. Michael's College
Colchester, Vermont, USA

11-12-09

Abstract: This paper considers whether high schools in competitive environments use grade inflation to attract and retain families, perhaps in addition to more constructive responses. Two measures of grade inflation are used: the cutoffs used by each school to assign a letter grade to a percent score; and high school GPA after controlling for test scores, a rich set of student and school characteristics, and (for a subset) college GPA. Two measures of competition are used: the enrollment-based concentration of school districts in metropolitan areas, and an instrument for this concentration. In both OLS and IV, increased competition significantly affects grade cutoffs: a one standard deviation increase in competition results in about a 0.12 to 0.18 standard deviation fall in the grade cutoffs (ceteris paribus, lower cutoffs yield higher grades). However, in both OLS and IV, competition does not significantly affect the actual assigned grades as measured by GPA. This pattern of results suggests that school administrators under competitive pressure may ease grade standards, but that teachers may re-adjust their scoring to leave actual grades relatively unchanged.

1 Introduction

1.1 Overview

Many economists see increased competition as an important way to reform a hidebound and underperforming public school system. Accordingly, over the past decade or more, much research activity has been devoted to estimating the effects of enhanced choice on public schools. These studies ask whether competition raises public school productivity, and largely ignores alternative responses to competition. Likewise, studies on grade inflation focus on the college level, and have not explored the impact of competition among schools. This paper fills both gaps by considering whether high schools facing more competition use grade inflation as a way to attract and retain families. It is the first paper to use U.S. data to bridge this gap between the school choice literature and the grade inflation literature.

Methodologically, this paper follows Hoxby (2000) in using traditional forms of school choice (specifically, Teibout choice among public districts) as an analogue for the effects of a school voucher plan. This framework embodies several common assumptions, which will be shared by this paper. These assumptions are that school administrators do not maximize the same objectives as parents; that school administrators receive some sort of fiscal or political benefit from strong demand for housing in their district; and that parents will optimize by choosing their district, if this choice can be exercised at low cost.

This paper first outlines several ways in which inflated grades could attract families to a district. Parents could naively think that higher grades reflect higher school or peer quality, or could strategically value higher grades for college admissions purposes. Second, this paper considers the different factors that affect the final grade – difficulty of the assignment, the rigor of grading, and the mapping of a score onto a letter grade – and addresses which factors may be vulnerable to inflation and how those interventions would show up in the data.

Data for this study come from the National Longitudinal Educational Survey (NELS:88), and are restricted to the survey subjects' high school years. Estimates are made for each of two measures of grade inflation. The first measure, the "grade cutoffs", captures interventions in the mapping of a score onto a letter grade, and is reported by principals at the school level. The second measure, the "assigned grade", captures the total output of the entire grading process and is given by the student's high-school GPA. Competition is measured by the enrollment-based concentration ratio (Herfindahl) of districts within Census Metropolitan Statistical Areas (MSAs). The Herfindahl will be endogenous if, just as this paper expects, families sort into inflating districts within an MSA. Therefore, the estimates are repeated using the Hoxby streams variable to instrument for district fragmentation.

For both OLS and IV, competition is associated with lower (easier) grade cutoffs. A one-standard-deviation increase in fragmentation lowers grade cutoffs by about .12 to .18 standard deviations. For both OLS and IV, competition seems to have little impact on the assigned grade. This pattern of results suggests that increased competition induces school administrators to lower grading standards (the grade cutoff results), but that teachers may respond by adjusting the rigor of their assignments or scoring (the weak assigned grade results).

1.2 Background

Grade inflation and school competition have both received tremendous attention from economists in recent years. However, research on these topics has largely proceeded on parallel tracks. Only one paper has looked at the intersection of these processes, and none have considered that intersection in the United States.

Research on school choice has focused on two possible effects of enhanced parental choice. The first effect is increased public school productivity resulting from competitive pressures, whether from other public school districts (Hoxby, 2000 and 2003; McMillan & Bayer, 2005) or private schools. The second effect is the possibility of adverse sorting by ability (Epple & Romano, 1998; Hsieh & Urquiola, 2005). Much of the analysis of choice's effect on productivity in the U.S. context has followed the "Hoxby model". This approach uses variations in traditional forms of school choice – such as residential choice among public school districts – to identify the impact of competition on public-school outcomes. While subject to some debate, these results generally show higher public outcomes resulting from competition (Hoxby 2000, McMillan & Bayer 2005). This finding is bolstered by Rouse, Hannaway, Goldhaber, & Figlio (2007), which finds that "failing" schools in Florida that are threatened with a voucher system undertake significant and productive reforms. However, very few studies have considered non-productive ways schools may respond to competition. In an environment where parents have imperfect information or do not maximize academic rigor, these alternatives could include lobbying for increased funding (Arum, 1996), enhanced sports programs, cosmetic improvements in school facilities, or grade inflation.

Research on grade inflation has focused primarily on the college level. Economists have thoroughly characterized the dynamics between professors, disciplines, and institutions that contribute to grade inflation at that level (Sabot & Wakeman-Linn, 1991; Yip & Yang 2003; Chan, Hao, and Suen, 2007). The role of student evaluations of professors has been highlighted as a major contributor to grade inflation (Kanagaretnam, Mathieu, & Thevaranjan, 2003). However, much less attention has been given to grade inflation at lower levels. While a discussion of grade inflation in kindergarten would clearly be misplaced, grade inflation may be measurable and relevant at the high school level.

The school-choice literature lacks a treatment of alternative responses to competition, while the grade-inflation literature neglects how the dynamic operates on the high-school level. The only paper to fill both gaps is Wikstrom & Wikstrom (2005), which looks at the impact of school choice on grade inflation in Sweden. They find that competition leads to modest grade inflation. This paper bridges the same gap using U.S. data, by considering whether public schools respond to greater competition by engaging in grade inflation.

2 The link between school choice and grade inflation

In a competitive setting, how would grade inflation benefit a school or school district? The following common assumptions are necessary. First, school administrators are assumed to maximize their own welfare, which may be at odds with producing the best education at the lowest cost. Second, school administrators are assumed to value increased demand for housing in their school district or increased enrollment, either because their budgets will increase or because their political superiors will be pleased. Third, even if existing families face costs to switching school districts, newly-established households or households moving to a region will maximize their welfare by choosing among school districts. This paper will make two additional assumptions: that parents can observe the grades awarded by various school districts, if only on an anecdotal or small-sample basis; and that district-level policymakers have *some* influence over grading policies and grading scales, if not the actual grades received by individual students.

The first two channels through which grade inflation could attract parents can be called *naive selection*. Here, it is assumed that i) parents observe school characteristics other than grades with error, ii) parents do not suspect grade inflation, and iii) parents do not observe more objective instruments like test scores. If this is the case, parents may think inflated grades are accurate, and are an indicator of school quality: "*You should move to our district. Our Jenny gets straight A's, so the schools must be good*." Alternatively, parents may think inflated grades are accurate, and are an indicator of student peer quality: "*You should move to our district. Our Jenny is surrounded by students who get straight A's.*"

One may object that, in the post-NCLB world, relatively objective information on school performance is readily available in the form of published test scores. This should reduce the salience of the first two channels. However, even where parents observe school quality accurately there are other channels through which grade inflation could attract parents. These channels can be called *strategic selection*. One such possibility is that parents see inflated grades as an advantage in college admissions: "*You should move to our district. Our Jenny got straight A's, and that got her into Bigshot U.*"

A final channel would exist if the attractiveness of inflated grades is heterogeneous across families. In particular, suppose that one or more of the above channels operated more strongly for high-ability families. For instance, highly-educated parents with high-achieving students may be more attracted by high perceived school quality or college-admissions gamesmanship than average families. If this is so, a grade-inflating school district could not only attract *more* families, but could attract a particular *type* of family. The peer quality and achievement of the district would be *genuinely* high, not because of school quality effects but because of selection. This high peer quality and high achievement would induce further demand for the school district.

One possible objection to these assumptions is that grades are at best observed anecdotally by parents. Moreover, even when grades are observed, the disadvantaged families who are targeted by prospective voucher plans may not select based on grades. However, theory predicts that producers raise quality for all when they are competing for even a small number of marginal consumers. Schneider et al (1998) find evidence for this theory in the school choice context.

Before turning to the empirical estimation, we should develop an idea of how a policy of grade inflation would be implemented. The grading process consists of several “moving parts”, which are differentially vulnerable to inflation and may offset one another. The first factor in the process is the difficulty of the assignment or exam, over which both the teacher and administrators may have influence. The next factor is the rigor of scoring, which would be invariable for mathematical subjects or multiple-choice tests, but could exhibit variation in essays, projects, and partial credit. It is likely that teachers have the most influence, and administrators have the least influence, at this stage. Finally, a number score must be mapped onto a letter grade using grade cutoffs. Here, administrators are likely to have their strongest influence, by setting school-wide or district-wide cutoff rules.

When asking whether school administrators have inflated grades in response to competition, there are essentially two questions. First, did the administrators change the factors over which they had the most control: lowered grade cutoffs. Second, did those interventions win out over the other factors to actually produce higher assigned grades? Plausible scenarios would include both lower grade cutoffs and higher assigned grades, or lower cutoffs that were offset by other factors to yield no inflation in assigned grades. On the other hand, unchanged cutoffs would raise serious doubts about a finding of higher assigned grades.

3 Empirical Strategy

As just discussed, “grade cutoff” measures and “assigned grade” measures of inflation are complements rather than substitutes when investigating whether administrators seek to inflate grades. Accordingly, two such measures will be developed, and each estimated separately.

3.1 Data

The primary data for this study comes from the National Educational Longitudinal Survey (NELS:88). This dataset consists of individual-level observations of more than 20,000 students who were 8th graders in 1988. In that base year, more than 1,000 schools were randomly sampled within each geographical strata. Parents provide family background data, including family size and composition, income, their own education, and attainment expectations. Principals provide information on school-level policies, programs, and student composition. Follow-up surveys were conducted in the 10^{th} and 12^{th} grades, and student high school transcripts are available. Surveyed students also took a series of standardized tests designed exclusively for the NELS survey. These tests were scored by NELS staff, and their results were not made available to parents. NELS also provides each student's entire high school transcript, as well as student- and family-level variables from the 1^{st} (10^{th} grade) follow-up. Additionally, data on the enrollment of school districts within each Census Metropolitan Statistical Area (MSA) was obtained from data in the National Center for Education Statistics' 1990 Common Core of Data database. This data was then used to calculate the enrollment-based concentration ratio for each MSA. Observations in NELS:88 that did not reside in a Census MSA were excluded. Finally, Hoxby's streams variables and metro-area characteristics for the IV 1^{st} stage are taken from a dataset she has made publicly available to holders of NCES restricted data licenses.

3.2 Grade Cutoffs

We first consider the step of the grade-assignment process where administrators may have the most impact, the mapping of a numerical score onto a letter grade. In this case, define L_s as the numerical cutoff point between letter grades. A lower L_s (the highest C is 79% rather than 83%, for example) will bring about higher letter grades if all else is held equal. We can then estimate the following *school-level* regression:

$$L_s = \lambda_0 + \lambda_c C_m + \lambda_h S_{sm} + \lambda_m M_m + \sigma_s \qquad (1)$$

where C_m is the level of competition (as indexed by 1 minus the enrollment-based concentration ratio[1] of districts with the MSA) faced by school s in metro area m; S is a vector of school-level

[1] The concentration ratio is the Herfindal index. Therefore, the measure of competition is: $1-\left[\sum_{\text{districts in MSA}} \left(\frac{\text{district enrollment}}{\text{total MSA enrollment}}\right)^2\right]$ This index has a value of 0 if there is only one large district, and a value of if every student is in a unique district.

characteristics; and M is a vector of MSA-level characteristics. In this setting, λ_c would be *negative* and significant if increased competition caused grade inflation.

Principals at each high school in the sample report the numerical score for the “Highest B”, “Highest C” and “Highest D”. These values are used for L_s in three separate regressions.
At the school level, covariates reduce noise by controlling for school-specific factors that could affect grade cutoffs. These covariates include the percent of students qualifying for free lunch, school racial breakdown, school percent of families with high income, school percent of families with high parental education, school share of parents who contact the school about grades, school average math and reading standardized test scores, student-teacher ratio, and lowest teacher salary. Covariates at the MSA level must control for factors that may be correlated with fragmentation, and could also affect the types of families or administrators attracted to the MSA. These include MSA population, MSA land area, and MSA mean income.

Private schools face even more competitive pressure than public schools – needing to attract tuition-paying families – and the effect of this pressure on their grades should be considered. Moreover, as discussed in Hoxby (2000 and 2005), the selection of students into private schools is itself endogenous to public district fragmentation. Removing private schools from the sample could therefore create selection bias the estimates for public schools. Although they operate outside the competition-between-public-districts framework, private schools are therefore included, and a dummy variable for private schools is used. Nevertheless, results for estimates restricted to just public schools (not shown) were not significantly different.

3.3 Assigned Grades

The second measure of grade inflation considers the grade itself, which is the output of the entire grade-assignment process, Suppose that the structural equation at the *individual* level is given by:

$$G_{si} = \gamma_0 + \gamma_A A_{si} + \gamma_x X_i + I_s + \varepsilon_{si} \qquad (2)$$

$$I_s = \theta_0 + \theta_c C_m + \theta_h H_s + \theta_m M_m + \psi_s \qquad (3)$$

G is grade-point average, A is the student's true academic achievement, X is a vector of student and family characteristics, I is possible school-level inflation, C is the degree of competition faced by the school, H is a vector of school-level characteristics, and M is a vector of MSA-level characteristics. The question at hand is whether θ_c is positive and significant. I is unobserved by the econometrician, which makes it impossible to estimate Equation (3) directly. Instead, equation (3) is substituted into Equation (2):

$$G_{si} = (\gamma_0 + \theta_0) + \gamma_A A_{si} + \gamma_x X_i + \theta_c C_m + \theta_h H_s + \theta_m M_m + (\varepsilon_{si} + \psi_s) \qquad (4)$$

As before, the degree of school competition is given by one minus the enrollment-based concentration (Herfindahl) of districts within the MSA. Student and family characteristics (X) again reduce noise, and also control for factors correlated with both GPA and competition. These include student gender and race; indicators for honors-track courses; teacher-reported variables regarding student absence and completion of work; indicators of physical or learning disabilities; student's hours spent on homework/studying and extracurriculars; student's opinion on "whether grades are important"; family income; parental marital status; and parental education. Again, school covariates must control for school-specific factors that could affect grade inflation. These include the percent of students qualifying for free lunch, student-teacher ratio, and lowest teacher salary. School-wide averages of family characteristics would be redundant, as they are simply linear combinations of the individual characteristics already included.   Private schools are included in the sample and given a dummy for the same reasons as in Section 3.2: selection into private schools is endogenous to district fragmentation, leading to selection bias if private schools are excluded.

Academic achievement A is also unobserved. Suppose that, as school choice advocates maintain, schools respond to competition with reforms that genuinely raise achievement. With no controls for achievement, this biases the estimate of θ_c. Schools in highly competitive areas would appear to be inflating, when they are in fact attracting high-ability students or raising genuine achievement. Several approaches will be taken to deal with this potential bias. First and simplest is to introduce direct controls for achievement: a vector of scores on standardized tests in reading, math, science, and social studies (T_{si})[2].   This approach yields the following regression equation:

$$G_{si} = \alpha_0 + \alpha_T T_{si} + \alpha_x X_i + \alpha_c C_m + \alpha_h H_s + \alpha_m M_m + \omega_{si} \quad (5)$$

These controls create a simple test for the extent to which bias exists, as will be discussed in the Results section. Any control will reduce bias in proportion to its correlation with the unobserved variable. While test scores are undoubtedly better than nothing, their correlation with unobserved achievement is probably not high enough to eliminate bias. Two further methods are employed: controlling for college GPA in a specification restricted to college attendees, and controlling for specific school policies. College GPA is likely to be more closely correlated with academic ability than test scores, and including it yields:

[2] Some might argue that test scores are actually *more* observable to parents than GPA, and are therefore more susceptible to inflation than GPA. While this may be true for some tests, the tests in this dataset were designed, administered, and graded by the NELS staff specifically for the survey. Their contents were not known to teachers in advance, and the results were not made public

$$G_{si} = \delta_0 + \delta_T T_{si} + \delta_R R_{si} + \delta_x X_i + \delta_c C_m + \delta_h H_s + \delta_m M_m + \nu_{si} \quad (\textit{restricted to college attendees}) \qquad (6)$$

where R is college GPA. Obviously, restricting to college attendees introduces a different set of issues. If (as will be shown in the Results section) grade inflation is concentrated at the high end of the grade distribution (B's turn into A's, but D's don't turn into C's), college-bound students would experience stronger effects. On the other hand, those who attend college must by definition have above-average GPAs. This restriction significantly reduces the variance in GPA, while variance in fragmentation is virtually unaffected. This pattern pushes the coefficient on fragmentation towards zero. Nevertheless, the presumably high correlation between college GPA and academic achievement makes this control a complement to simple test scores.

If the correlation between unobserved true achievement and competition is driven primarily by achievement-enhancing policies adopted by schools under pressure, a final additional strategy is possible. Rouse, Hannaway, Figlio, and Goldhaber (2007) look at school policies that are put in place as a response to a "Failing" grade in the Florida school assessment system, which grants vouchers to students in such schools. They find that such schools adopt additional policies aimed at low-performing students, lengthen instructional time, and optimize scheduling systems. Indicators for many of these policies are included in the NELS dataset. This allows the following equations to be estimated:

$$G_{si} = \gamma_0 + \gamma_T T_{si} + \gamma_x X_i + \gamma_c C_m + \gamma_h H_s + \gamma_p P_s + \gamma_m M_m + \omega_{si} \qquad (7)$$

Where P is a vector of indicators for school policies associated with competition threats. Intuitively, if two students' test scores and observables are identical, *and their schools are pursing the same policies*, then remaining variation in GPA is likely to be inflation. As will be discussed in the Results section, this control creates a simple test for the magnitude of the bias.

3.4 Sorting and Endogenous Competition

Assume that grade inflation varies idiosyncratically by district *within* an MSA, and that inflated grades are attractive to at least some parents. In this environment, there are two ways the Herfindahl-based Competition Index can be biased. The most serious of these arises if, as this paper assumes, at least some families will sort into the inflating districts in an MSA. Such sorting raises the average grade level in the MSA. As noted in Hanuskek & Rivkin (2003), this sorting also mechanically changes the herfindahl-based Competition Index. If the more-inflating districts are larger/smaller than average, the Competition Index will fall/rise. This would associate inflation with lower/higher competition, introducing the corresponding biases in the estimation. Thus, *if families behave in exactly the way this paper assumes*, the measure of competition is highly endogenous. Endogenous district formation is the second, and perhaps less likely, source of bias in the Herfindahl. Akin to the process noted by Hoxby (2000), endogenous district formation arises when inflating districts attract mergers, and deflating districts cause splits. This process results in a negative correlation between fragmentation and inflation, leading to a bias against finding that fragmentation causes inflation.

Endogenous family sorting within MSA or endogenous district formation can be addressed by an instrument that is correlated with fragmentation but not with grade inflation. Such an instrument is available in the streams measure introduced by Hoxby (2000). This instrument is the focus of considerable controversy (Rothstein 2005, Hoxby 2005), but a full resolution of this debate is beyond the scope of the present paper. Given the arguments made in Hoxby (2000 and 2005), the streams instrument seems well suited to affect district fragmentation without correlation with grade inflation. To test this instrument, this paper will simply focus on the common assessments of instruments, such as the strength of the 1st stage and Hausman tests.

The IV approach for both grade-inflation measures is to estimate a MSA-level first stage:

$$C_m = \phi_0 + \phi_s S_m + \phi_m M_m + \omega_m \tag{9}$$

Where C_m is the Herfindahl-based choice index for metro area m, S_m is the number of streams in area m, and M_m is a set of metro-area characteristics. Six different versions of Equation (9) are run: one on the school-level sample used for the grade cutoffs, and five on the individual-level specifications used in the five "assigned grade" equations. The 2nd stage for the grade cutoffs measure would be again estimated on the school level using predicted competition from the corresponding version of Equation (9):

$$L_s = \tau_0 + \tau_c \hat{C}_m + \tau_h S_{sm} + \tau_m M_m + \sigma_s \tag{10}$$

Recall, τ_c would be *negative* and significant if increased competition caused grade inflation. Likewise, the 2nd stage for the assigned grade is to estimate the following individual level equations using predicted competition from the corresponding version of Equation (9):

$$G_{si} = \varphi_0 + \varphi_T T_{si} + \varphi_x X_i + \varphi_c \hat{C}_m + \varphi_h H_s + \varphi_m M_m + \omega_{si} \tag{11}$$

Here, φ_c would be *positive* and significant if increased competition caused grade inflation. Equation (11) is the baseline 2nd stage for assigned grades. Similar 2nd stage equations, using the predicted fragmentation from the corresponding versions of Equation (9), are estimated for the other four assigned grade specifications.

4 Results

4.1 Grade Cutoffs – OLS

Table 3 shows the results from estimating Equation (1) separately for each of three principal-reported grade cutoffs. These estimates are done at the school level. The interpretation of the coefficient on MSA-level choice in Highest B, for example, is that the B+/A- cutoff would be 1.6 points lower in an MSA with maximum fragmentation than in a MSA with one monolithic district. In standardized terms, a one-standard-deviation rise in fragmentation lowers the B+/A- cutoff by .18 standard deviations, lowers the C+/B- cutoff by .12 standard deviations, and lowers the D+/C- cutoff by .07 standard deviations. The only other school-level variable that significantly affects grade cutoffs is the student/teacher ratio: a 1-student rise in this ratio lowers the B+/A- cutoff by .12 points. One interpretation of this finding is that school systems try to compensate for unattractive student/teacher ratios with attractive grades.

4.2 Assigned Grades – OLS

Table 4 shows selected[3] results from estimating Equations (5) – (8), along with an equation that omits any controls for achievement, at the individual student level. The interpretation of this coefficient in Equation (5), for example, is that average high school GPAs would be .006 points (out or 4.0) higher in an MSA with maximum fragmentation than in a MSA with one monolithic district. In standardized terms, a one-standard-deviation increase in fragmentation would result in a .01-standard-deviation increase in GPA. More importantly, however, the coefficient on MSA-level choice is insignificant in all five specifications. If bias resulting from a correlation between unobserved achievement and choice were a major factor, we would observe significant

[3] Results for the following covariates are suppressed to shorten Table 4 to two pages: student physical handicap, family subscribes to newspaper, family owns computer, four categorical dummies for frequency of student absences, three categorical dummies for importance student places on grades, whether student attends class without materials, and three categorical dummies for how often student fails to turn in homework.

movement in the coefficient when (even imperfect) ability and school policy controls were introduced. Instead, there is no significant difference in the coefficient between the baseline specification (Equation 5), the specification that includes controls for school policies (Equation 6), and the specification that omits any controls for ability ("No Ability Controls"). In the specifications that include college GPA (and are thus restricted to college attendees), the coefficient is negative and insignificant. Without reading too much into an insignificant result, this is likely an artifact of selection. College attendees must have higher high school GPAs, which may combine with effect heterogeneity to produce a different estimate than the full sample.

4.3 IV

The 1^{st} stage of the IV estimation regresses the Metro Area Competition Index on the number of large and small streams in the MSA, as well as MSA characteristics that could also contribute to fragmentation. Following Hoxby (2000), this 1^{st} stage is estimated on the individual level, which provides a more efficient estimation. Results of the 1^{st} stage are given in Table 5. The first column gives the 1^{st} stage for the grade cutoff (school-level) specification, while the 2^{nd} column reports the 1^{st} stage for the baseline assigned grade (individual-level) specification. The 1^{st} stages are strong, with a highly significant coefficient on the number of streams, and high joint significance of all RHS variables. Differences in point estimates between these estimations and Hoxby's 1^{st} stage result from having different 2^{nd} stages (covariates of which are naturally included in the 1^{st} stage), and minor improvements to Hoxby's dataset since the publication of her 2000 paper.

4.4 Grade Cutoffs – IV

Table 6 shows selected 2^{nd}-stage IV results for the three grade cutoff regressions. In each case, the coefficient on the choice index is again negative and significant. The interpretation of the coefficient on MSA-level choice in Highest B, for example, is that the B+/A- cutoff would be 3.0 points lower in an MSA with maximum fragmentation than in a MSA with one monolithic district. In standardized terms, a one-standard-deviation rise in fragmentation lowers the B+/A- cutoff by .34 standard deviations, lowers the C+/B- cutoff by .27 standard deviations, and lowers the D+/C- cutoff by .22 standard deviations. The IV estimate is significantly greater in magnitude than its OLS counterpart for the C+/B- cutoff and the D+/C- cutoff, suggesting that OLS is biased downwards for the grade cutoff measure. Hausman tests reject the equivalence of IV and OLS for all three cutoffs.

4.5 Assigned Grades – IV

Table 7 shows selected[4] results for the 2^{nd}-stage IV for the assigned-grade regressions, using the same five specifications as in Table 3. In all specifications, the coefficient on predicted MSA-level competition is negative but insignificant. This suggests that OLS had a slight upward bias for assigned grade.

4.6 IV vs. OLS Results

Competition lowers grade cutoffs in both OLS and IV. By contrast, competition has no effect on assigned grades in OLS or IV. There is evidence for downward bias in OLS for grade cutoffs, but upward bias in OLS for assigned grades. What scenarios could explain this pattern of results?

[4] Results are suppressed for the same covariates as in Table 4.

Focus first on the difference between the two measures of grade inflation. These results indicate that administrators respond to competition by lowering grade cutoffs, but that the assigned grades are unchanged. In light of the multiple factors that determine a grade, this is consistent with teachers re-calibrating the assignments or the scoring to offset the lowered grade cutoffs.

Next, what scenarios could explain a downward bias in OLS for grade cutoffs, and an upward bias in OLS for assigned grades? Based on the discussion in Section 3.5 (summarized by Figure 1), sorting of family or administrator types between MSA and sorting of families within MSA could produce either positive or negative biases. The observed difference in biases is most likely due to the fact that administrators act on different factors than families. If easy-grading administrators are attracted to less-fragmented MSAs, OLS would be biased down for grade cutoffs. Meanwhile, if idiosyncratically inflating districts within an MSA are relatively small, and attract families, then the measure of fragmentation would rise. The association of higher fragmentation and easy grading would bias OLS upwards for assigned grades.

5 Conclusions

Many economists have considered the dynamics of grade inflation and school choice separately. This is the first paper to use U.S. data to ask whether schools inflate grades in response to greater competition. It lays out several different channels through which inflated grades could attract families, some of which assume naive families, and some which allow families to be complicit in the inflation.

Empirically, this uses two definitions for grade inflation: grade cutoffs used to map scores onto letter grades, and the residuals from a regression of high-school GPA on test scores and a rich set of student/family characteristics. Two measures of competition are also used: a MSA competition index based on the enrollment-weighted herfindahl of districts within the MSA, and the Hoxby streams instrument to overcome the endogeneity of this index.

In OLS, a more fragmented MSA is associated with both lower grade cutoffs and higher grade residuals. The grade cutoff results are moderate in magnitude, while the grade residual results have weak magnitude and very low R^2. In IV, the grade cutoff results grow stronger in both magnitude and significance, while the grade residual results become insignificant. This pattern of results suggests that administrators do lower grading standards in response to competition, but that these interventions are offset by teacher adjustments, yielding unchanged assigned grades.

These results may find favor (or disfavor!) with both sides of the school choice policy debate. School choice critics may point out that administrators do appear to lower grade standards in the face of competition. Choice proponents can nevertheless claim that the final assigned grades are unaffected by these interventions. If the final assigned grades are what matter for forming student habits and sending signals of student quality, these results suggest that grade inflation is not a crippling side-effect of enhanced choice.

References

Arum, Richard. Do Private Schools Force Public Schools to Compete? *American Sociological Review*, 61(1). 1996

Chan, William, Li Hao, Wing Suen. A Signalling Theory of Grade Inflation. International Economic Review, 48(3). 2007.

Epple, Dennis & Richard Romano. Competition between Private and Public Schools, Vouchers, and Peer-Group Effects. *American Economic Review*, 88(1). 1998.

Hanushek, Eric and Steven Rivkin. Does Public School Competition Affect Teacher Quality? In "The Economics of School Choice", Caroline Hoxby ed. University of Chicago Press, 2003.

Hoxby, Caroline. Does Competition among Public Schools Benefit Student and Taxpayers? *American Economic Review*, 90(5). 2000

Hoxby, Caroline. School Choice and School Productivity: Could School Choice Be a Tide that Lifts All Boats? In "The Economics of School Choice", Caroline Hoxby ed. University of Chicago Press, 2003.

Hoxby, Caroline. Competition among Public Schools: A Reply to Rothstein. NBER Working Paper #11216, 2005.

Hsieh, Chang-Tai, and Miquel Urquiola. When Schools Compete, How do They Compete? An Assessment of Chile's Nationwide School Voucher Program. NBER Working Paper #10008. 2003

Kanagaretnam, Kiridaran, Robert Mathieu and Alex Thevaranjan An Economic Analysis of the Use of Student Evaluations: Implications for Universities. *Managerial and Decision Economics,* 24(1). 2003.

McMillan, Robert and Patrick Bayer. Choice and Competition in Local Education Markets. NBER Working Paper #11802. 2005.

Rothstein, Jessie. Does Competition Among Public Schools Benefit Students and Taxpayers? A Comment on Hoxby (2000). NBER Working Paper #11215, 2005.

Rouse, Cecilia Elena, Jane Hannaway, Dan Goldhaber, & David Figlio. Feeling the Florida Heat? How Low-Performing Schools Respond to Voucher and Accountability Pressure. National Center for Analysis of Longitudinal Data in Education Research (CALDER) Working Paper 13. 2007

Sabot, Richard and John Wakeman-Linn. Grade Inflation and Course Choice. *The Journal of Economic Perspectives*, 5(1). 1991.

Schneider, Mark, Paul Teske, Melissa Marschall, & Christine Roch. Shopping for Schools: In the Land of the Blind, The One-Eyed Parent May Be Enough. *American Journal of Political Science*, 42(3). 1998

Wikstrom, Christina & Magnus Wikstrom. Grade inflation and School Competition:an Empirical Analysis Based on the Swedish Upper Secondary Schools. *Economics of Education Review*, 24(3). 2005.

Yang, Huanxing and Chun Seng Yip. An Economic Theory of Grade Inflation. University of Pennsylvania Working Paper. 2002. http://www.econ.upenn.edu/~yipcs/gradeinflationv2.pdf

Figure 1: Sources of Possible Bias, Direction of Bias, and Possible Solutions

Description of bias	*Grade Inflation Measure that is affected*	*Is bias against or in favor of finding competition-inflation link?*	*Solution*
Unobserved student or school quality is correlated with fragmentation	GPA	in favor	control for college GPA, school reforms
Dynamics within MSAs			
Endogenous district formation	Both	against	Instrument for fragmentation
Inflating districts attract families, which changes Herf and avg. grade	Both	either	Instrument for fragmentation

Table 1: Summary Statistics: Grade Cutoff Regressions

	mean	*std. dev.*
School Highest B	90.457	2.023
School Highest C	80.953	3.298
School Highest D	71.472	4.507
Metro Area Fragmentation Index	0.768	0.221
School Private	0.079	0.253
Student/Teacher ratio	16.355	3.849
School % Free lunch	17.320	19.167
School Salary of lowest-paid teachers (thousands)	20.573	3.447
School avg.Reading test score	51.359	5.647
School avg.Math test score	51.917	5.994
School avg. Science test score	0.162	0.213
School avg. Social Studies test score	0.186	0.248
School avg. parents contact school about grades	0.519	0.254
School % Male	0.510	0.243
School % Black	0.130	0.265
School % Hispanic	0.116	0.226
School % Asian	0.070	0.138
School % $50K < Family income < $75K	0.065	0.131
School % Family income > $75K	0.272	0.235
School % Parent has some college (relative to no HS diploma)	0.234	0.217
School % Parent has college degree (relative to no HS diploma)	0.361	0.250

Table 2: Summary Statistics: Assigned Grade Regressions

	mean	*std. dev.*
High School GPA	2.696	0.665
Metro Area Fragmentation Index	0.780	0.225
Reading test score	51.989	9.772
Math test score	52.742	9.834
Science test score	52.253	9.819
Social Studies test score	52.011	9.793
College GPA	2.706	0.734
English reading ability	0.969	0.173
Male	0.503	0.500
Black	0.068	0.251
Hispanic	0.096	0.295
Asian	0.067	0.250
Family income < $10K (relative to $10K - $25K)	0.207	0.405
$25K < Family income < $50K (relative to $10K - $25K)	0.184	0.388
$50K < Family income < $75K (relative to $10K - $25K)	0.061	0.239
Family income > $75K (relative to $10K - $25K)	0.129	0.335
Parent has HS diploma (relative to no HS diploma)	0.375	0.484
Parent has some college (relative to no HS diploma)	0.260	0.439
Parent has college degree (relative to no HS diploma)	0.244	0.430
Single Parent	0.201	0.401
LD diagnosed	0.051	0.221
High track, English	0.161	0.368
High track, Math	0.180	0.385
Parents contact school about grades	0.492	0.500
Family rule about maintaining GPA	0.721	0.449
Student Absences = 0 (relative to 3 or 4 days)	0.149	0.356
Student Absences = 1 or 2 days (relative to 3 or 4 days)	0.248	0.432
Student Absences = 5 to 10 days (relative to 3 or 4 days)	0.222	0.415
Student Absences > 10 days (relative to 3 or 4 days)	0.091	0.288
Student usually fails to completes homework (relative to "seldom")	0.051	0.221
Student often fails to completes homework (relative to "seldom")	0.129	0.335
Student never fails to completes homework (relative to "seldom")	0.196	0.397
Private	0.044	0.206
Student/Teacher ratio	16.143	3.710
% Free lunch	13.642	16.034
Salary of lowest-paid teachers (thousands)	20.397	3.233
MSA population (thousands)	1,744	2,255
MSA area (square miles)	2547	2118
MSA average log income	3.608	0.164

Table 3: Grade Cutoffs, OLS

	Highest B	Highest C	Highest D
Metro Area Fragmentation (1 - herfindahl)	-1.600 ***	-3.108 **	-1.953
	(0.593)	(1.376)	(1.369)
Private	-0.472	-0.101	0.083
	(0.419)	(0.837)	(0.994)
Student/Teacher ratio	-0.121 ***	-0.175 ***	-0.250 ***
	(0.033)	(0.059)	(0.074)
% Free lunch	-0.011 *	-0.045 *	-0.052 **
	(0.006)	(0.023)	(0.025)
Salary of lowest-paid teachers (thousands)	-0.036	0.009	-0.020
	(0.035)	(0.120)	(0.123)
School Avg. Reading Score	-0.039 **	-0.023 **	0.001
	(0.018)	(0.049)	(0.050)
School Avg. Math Score	0.025	0.025	0.006
	(0.018)	(0.059)	(0.060)
School % high math track	0.328	-1.132	0.769
	(0.462)	(2.500)	(2.331)
School % high english track	0.205	1.155	0.650
	(0.364)	(1.204)	(1.057)
School % parents contact regarding grades	0.230	-1.018	-1.654
	(0.326)	(1.412)	(1.446)
School % male	0.446	0.627	0.253
	(0.341)	(0.737)	(0.927)
School % black	0.664	-0.166	1.480
	(0.415)	(2.347)	(2.241)
School % hispanic	-0.987	-1.365	0.687
	(0.620)	(1.087)	(1.576)
School % Asian	-0.609	-1.910	-1.983
	(0.652)	(1.691)	(1.814)
School % families with \$50K < income < \$75K	0.427	0.296	-1.237
	(0.912)	(3.256)	(3.762)
School % families with \$75K > income	-0.399	-0.754	-0.766
	(0.499)	(0.911)	(1.137)
School % families with some college	-0.852 *	-2.779 *	-2.871 *
	(0.482)	(1.495)	(1.574)
School % families with college degrees	-0.185	0.557	0.484
	(0.628)	(1.091)	(1.348)
MSA Population, millions	0.020	0.057	0.036
	(0.071)	(0.140)	(0.019)
MSA Area, hundreds of Sq. Miles	0.003	0.004	0.007
	(0.003)	(0.006)	(0.008)
MSA mean income	-2.912 ***	-5.921 ***	-7.648 ***
	-0.833	(1.835)	(2.332)
Constant	105.780 ***	108.837 ***	106.591 ***
	(2.99)	(5.945)	(7.872)
Mean of Cutoff	90.457	80.953	71.472
Standardized coefficient on Fragmentation	-0.178	-0.116	-0.069
Observations	486	487	484
Adj. R^2	0.229	0.091	0.106

Table 4: Assigned Grades, OLS (Continued on next page)

	No controls	Eqn. (5)	Eqn. (6)	Eqn. (7)	Eqn. (8)
Fragmentation (1 - herfindahl)	0.0056	0.0064	0.0099	-0.0316	-0.0442
	(0.0591)	(0.0475)	(0.0493)	(0.0598)	(0.0611)
Reading test score		0.0040 **	0.0040 **	0.0013	0.0012
		(0.0016)	(0.0016)	(0.0020)	(0.0020)
Math test score		0.0240 ***	0.0240 ***	0.0219 ***	0.0219 ***
		(0.0016)	(0.0017)	(0.0021)	(0.0021)
Science test score		0.0019	0.0020	0.0011	0.0014
		(0.0017)	(0.0018)	(0.0021)	(0.0021)
Social Studies test score		0.0076 ***	0.0076 ***	0.0065 ***	0.0066 ***
		(0.0014)	(0.0015)	(0.0019)	(0.0019)
English reading ability	0.0302	-0.0540	-0.0387	0.0141	0.0383
	(0.0610)	(0.0534)	(0.0543)	(0.0775)	(0.0801)
Male	0.1368 ***	0.1843 ***	0.1830 ***	0.1243 ***	0.1242 ***
	(0.0198)	(0.0183)	(0.0185)	(0.0227)	(0.0231)
Black	-0.3931 ***	-0.2059 ***	-0.2073 ***	-0.1397 ***	-0.1435 ***
	(0.0433)	(0.0369)	(0.0381)	(0.0434)	(0.0449)
Hispanic	-0.1015 ***	-0.0309	-0.0289	-0.0403	-0.0428
	(0.0381)	(0.0358)	(0.0367)	(0.0413)	(0.0434)
Asian	0.0226	-0.0058	-0.0046	0.0292	0.0257
	(0.0406)	(0.0356)	(0.0367)	(0.0409)	(0.0419)
Family income < $10K (relative to $10K - $25K)	-0.0543 *	-0.0214	-0.0232	0.0012	0.0016
	(0.0303)	(0.0253)	(0.0259)	(0.0312)	(0.0326)
$25K < Family income < $50K (relative to $10K - $25K)	0.0269	0.0284	0.0319	0.0134	0.0152
	(0.0283)	(0.0252)	(0.0251)	(0.0300)	(0.0302)
$50K < Family income < $75K (relative to $10K - $25K)	-0.0588	0.0091	0.0085	0.0786	0.0764
	(0.0452)	(0.0392)	(0.0403)	(0.0677)	(0.0694)
Family income > $75K (relative to $10K - $25K)	-0.0153	-0.0040	-0.0058	0.0076	0.0075
	(0.0334)	(0.0294)	(0.0300)	(0.0345)	(0.0350)
Parent has HS diploma (relative to no HS diploma)	0.1382 ***	0.0715 **	0.0726 **	0.0500	0.0498
	(0.0341)	(0.0312)	(0.0315)	(0.0504)	(0.0503)
Parent has some college (relative to no HS diploma)	0.2281 ***	0.1032 ***	0.1047 ***	0.0835	0.0800
	(0.0378)	(0.0365)	(0.0370)	(0.0534)	(0.0538)
Parent has college degree (relative to no HS diploma)	0.3666 ***	0.1618 ***	0.1694 **	0.0793	0.0821
	(0.0395)	(0.0382)	(0.0391)	(0.0580)	(0.0588)
Single Parent	-0.0516 *	-0.0412	-0.0356	-0.0179	-0.0115
	(0.0282)	(0.0254)	(0.0259)	(0.0327)	(0.0336)
LD diagnosed	-0.2144 ***	0.0292	0.0235	-0.0174	-0.0176
	(0.0401)	(0.0370)	(0.0373)	(0.0452)	(0.0438)
High track, English	0.2730 ***	0.0816 ***	0.0823 ***	0.0627 ***	0.0604 **
	(0.0300)	(0.0248)	(0.0253)	(0.0261)	(0.0273)
High track, Math	0.2841 ***	0.0943 ***	0.1020 ***	0.0857 ***	0.0955 ***
	(0.0272)	(0.0234)	(0.0236)	(0.0253)	(0.0257)
Parents contact school about grades	-0.1249 ***	-0.0851 ***	-0.0871 ***	-0.0508 **	-0.0538 **
	(0.0208)	(0.0184)	(0.0189)	(0.0223)	(0.0230)
Family rule about maintaining GPA	-0.0960 ***	-0.0523 ***	-0.0511 ***	-0.0440 **	-0.0418 *
	(0.0214)	(0.0186)	(0.0190)	(0.0220)	(0.0228)

Table 4: Assigned Grades, OLS, Continued

	No controls	Eqn. (5)	Eqn. (6)	Eqn. (7)	Eqn. (8)
School: private	0.0275	-0.0277	-0.0137	0.0516	0.0536
	(0.0686)	(0.0644)	(0.0668)	(0.0599)	(0.0638)
School: student/teacher ratio	0.0117 ***	0.0143 ***	0.0135 ***	0.0109 **	0.0097 **
	(0.0045)	(0.0044)	(0.0044)	(0.0047)	(0.0046)
School: % free lunch	-0.0025 ***	-0.0005	-0.0006	0.0012	0.0012
	(0.0009)	(0.0009)	(0.0009)	(0.0012)	(0.0012)
School: lowest teacher salary	-0.0043	-0.0022	-0.0017	0.0018	0.0017
	(0.0060)	(0.0059)	(0.0058)	(0.0052)	(0.0052)
MSA Population, millions	-0.0073	-0.0078	-0.0083	-0.0087	-0.0088
	(0.0074)	(0.0060)	(0.0062)	(0.0068)	(0.0070)
MSA Area, hundreds of Sq. Miles	0.0004	0.0008	0.0010	0.0011	0.0015 *
	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0008)
MSA mean income	-0.0770	-0.1186	-0.1067	-0.0951	-0.0784
	(0.0961)	(0.0929)	(0.0960)	(0.0985)	(0.1019)
College GPA				0.2156 ***	0.2140 ***
				(0.0172)	(0.0175)
Length of school day			0.0005		0.0004
			(0.0003)		(0.0003)
School has professional tutors			0.0853		-0.1571 ***
			(0.0608)		(0.0561)
School has peer tutors			0.0137		-0.0035
			(0.0473)		(0.0495)
School has common prep periods for teachers			-0.0033		-0.0145
			(0.0393)		(0.0404)
School uses flex time for classes			-0.0536		-0.0219
			(0.0431)		(0.0432)
Math/Science Teacher certified in subject being taught			0.0482		0.0278
			(0.0514)		(0.0549)
Math/Science Teacher has degree in subject being taught			-0.0049		-0.0031
			(0.0227)		(0.0281)
Math/Science Teacher received no support for prof. development			0.0065		0.0172
			(0.0199)		(0.0241)
English/SS Teacher certified in subject being taught			-0.0101		0.0066
			(0.0471)		(0.0627)
English/SS Teacher has degree in subject being taught			-0.0494 **		-0.0402 *
			(0.0198)		(0.0234)
English/SS Teacher received no support for prof. development			-0.0067		-0.0121
			(0.0204)		(0.0231)
Constant	2.8307 ***	1.0066 ***	0.7959 **	0.6606 *	0.4778
	(0.3439)	(0.3308)	(0.3773)	(0.3656)	(0.4305)
Mean of GPA	2.696	2.696	2.696	2.696	2.696
Standardized coefficient on Fragmentation	0.016	0.010	0.010	-0.010	-0.016
Observations	3102	3102	3033	1705	1671
Adj. R^2	0.377	0.534	0.538	0.552	0.554

Note: For Tables 4 and 7, results for the following covariates are suppressed to shorten the tables to two pages: student physical handicap, family subscribes to newspaper, family owns computer, four categorical dummies for frequency of student absences, three categorical dummies for importance student places on grades, whether student attends class without materials, and three categorical dummies for how often student fails to turn in homework.

Table 5: IV First Stage

	Grade Cutoff specification		Assigned Grade specification	
Number of smaller streams (in hundreds)	0.0936	***	0.0984	***
	(0.0127)		(0.0048)	
Number of larger streams (in hundreds)	-0.0302	**	-0.0255	***
	(0.0133)		(0.0050)	
Population of Metropolitan area (in thousands)	0.0000		0.0000	***
	(0.0000)		(0.0000)	
Land area of Metropolitan area (in thousands of square miles)	0.0143	***	0.0126	***
	(0.0040)		(0.0017)	
Mean of log income of metropolitan area	-0.2892	**	-0.2214	***
	(0.1337)		(0.0461)	
Gini coefficient of metropolitan area	-5.2347	***	-4.5826	***
	(0.6996)		(0.2520)	
Share of metropolitan area that is black	0.9497	***	0.8519	***
	(0.2586)		(0.0969)	
Share of metropolitan area that is Asian	-0.9099	***	-1.0581	***
	(0.2466)		(0.0840)	
Share of metropolitan area that is Hispanic	0.5336	***	0.6206	***
	(0.1401)		(0.0525)	
Index of racial homogeneity of metropolitan area	0.4463	**	0.4428	***
	(0.1830)		(0.0688)	
Share of adults in metropolitan area with some college	-0.4287		0.1165	
	(0.3285)		(0.1131)	
Share of adults in metropolitan area with college degree	0.8218	***	0.9074	***
	(0.2757)		(0.1030)	
Index of educational homogeneity of metropolitan area	-2.9595	***	-1.7544	***
	(0.8350)		(0.3164)	
Constant	4.3796	***	3.3876	***
	(0.8007)		(0.2807)	
Indicator variables for the nine Census regions	Yes		Yes	
Covariates from 2nd stage	Yes		Yes	
Observations	537		3704	
Adj. R^2	0.468		0.496	
F	13.43		60.85	

Table 6: Grade Cutoffs, IV

	Highest B		Highest C		Highest D
Predicted Metro Area Fragmentation (1 - herfindahl)	-3.034	***	-7.305	***	-6.347
	(0.747)		(2.430)		(2.446)
Private	-0.765	*	-0.352		-0.263
	(0.419)		(0.769)		(0.952)
Student/Teacher ratio	-0.123	***	-0.179	***	-0.258
	(0.032)		(0.059)		(0.078)
% Free lunch	-0.005		-0.032		-0.036
	(0.006)		(0.022)		(0.022)
Salary of lowest-paid teachers (thousands)	-0.075	**	-0.058		-0.131
	(0.033)		(0.113)		(0.119)
School Avg. Reading Score	-0.043	**	-0.037		-0.013
	(0.020)		(0.052)		(0.055)
School Avg. Math Score	0.023		0.025		-0.004
	(0.019)		(0.064)		(0.066)
School % high math track	0.430		-0.796		1.326
	(0.498)		(2.596)		(2.431)
School % high english track	0.258		1.304		0.904
	(0.376)		(1.240)		(1.111)
School % parents contact regarding grades	0.239		-1.204		-1.870
	(0.330)		(1.516)		(1.540)
School % male	0.430		0.539		0.197
	(0.356)		(0.8122)		(1.015)
School % black	0.197		-1.230		0.026
	(0.435)		(2.346)		(2.219)
School % hispanic	-1.170	*	-1.865		-0.284
	(0.674)		(1.314)		(1.866)
School % Asian	-1.207		-3.310	*	-4.201
	(0.730)		(1.773)		(1.883)
School % families with \$50K < income < \$75K	0.530		0.619		-0.865
	(0.953)		(3.364)		(3.945)
School % families with \$75K > income	-0.695		-1.363		-1.854
	(0.513)		(0.957)		(1.185)
School % families with some college	-0.867	*	-2.865	*	-3.017
	(0.480)		(1.496)		(1.551)
School % families with college degrees	-0.403		0.286		0.305
	(0.646)		(1.111)		(1.357)
Constant	97.779		93.400		86.576
	(1.394)		(3.080)		(3.507)
Mean of Cutoff	90.457		80.953		71.472
Standardized coefficient on Fragmentation	-0.339		-0.273		-0.224
Observations	476		477		474
Adj. R^2	0.182		0.061		0.069

Table 7: Assigned Grades, IV (Continued on next page)

	No controls		Eqn. (5)		Eqn. (6)		Eqn. (7)		Eqn. (8)	
Predicted Fragmentation (1- herfindahl)	-0.0761		-0.1283		-0.1049		-0.1465	*	-0.1349	
	(0.0921)		(0.0883)		(0.0919)		(0.0884)		(0.0915)	
Reading test score			0.0041	**	0.0042	***	0.0016		0.0016	
			(0.0016)		(0.0016)		(0.0020)		(0.0020)	
Math test score			0.0240	***	0.0240	***	0.0219	***	0.0217	***
			(0.0017)		(0.0017)		(0.0021)		(0.0021)	
Science test score			0.0018		0.0018		0.0008		0.0010	
			(0.0018)		(0.0018)		(0.0021)		(0.0021)	
Social Studies test score			0.0075	***	0.0074	***	0.0064	***	0.0066	***
			(0.0015)		(0.0015)		(0.0019)		(0.0019)	
English reading ability	0.0347		-0.0470		-0.0318		0.0165		0.0377	
	(0.0597)		(0.0546)		(0.0555)		(0.0790)		(0.0813)	
Male	0.1373	***	0.1855	***	0.1844	***	0.1227	***	0.1218	***
	(0.0200)		(0.0188)		(0.0190)		(0.0232)		(0.0237)	
Black	-0.4169	***	-0.2294	***	-0.2300	***	-0.1600	***	-0.1631	***
	(0.0433)		(0.0374)		(0.0388)		(0.0438)		(0.0457)	
Hispanic	-0.1012	***	-0.0403		-0.0380		-0.0509		-0.0523	
	(0.0372)		(0.0368)		(0.0374)		(0.0419)		(0.0437)	
Asian	0.0198		-0.0216		-0.0194		0.0125		0.0117	
	(0.0398)		(0.0372)		(0.0382)		(0.0428)		(0.0435)	
Family income < \$10K (relative to \$10K - \$25K)	-0.0488		-0.0199		-0.0207		-0.0037		-0.0006	
	(0.0296)		(0.0257)		(0.0263)		(0.0317)		(0.0332)	
\$25K < Family income < \$50K (relative to \$10K - \$25K)	0.0248		0.0240		0.0277		0.0064		0.0087	
	(0.0282)		(0.0256)		(0.0255)		(0.0303)		(0.0307)	
\$50K < Family income < \$75K (relative to \$10K - \$25K)	-0.0534		0.0076		0.0090		0.0649		0.0665	
	(0.0447)		(0.0391)		(0.0404)		(0.0671)		(0.0691)	
Family income > \$75K (relative to \$10K - \$25K)	-0.0162		-0.0061		-0.0068		0.0079		0.0084	
	(0.0334)		(0.0297)		(0.0302)		(0.0344)		(0.0348)	
Parent has HS diploma (relative to no HS diploma)	0.1445	***	0.0791	**	0.0809	**	0.0635		0.0652	
	(0.0336)		(0.0320)		(0.0321)		(0.0507)		(0.0507)	
Parent has some college (relative to no HS diploma)	0.2275	***	0.1061	***	0.1083	***	0.0888	*	0.0873	
	(0.0371)		(0.0371)		(0.0376)		(0.0537)		(0.0543)	
Parent has college degree (relative to no HS diploma)	0.3759	***	0.1698	***	0.1784	***	0.0916		0.0962	
	(0.0396)		(0.0392)		(0.0401)		(0.0588)		(0.0600)	
Single Parent	-0.0463		-0.0421		-0.0369		-0.0160		-0.0112	
	(0.0283)		(0.0260)		(0.0265)		(0.0335)		(0.0342)	
LD diagnosed	-0.2245	***	0.0208		0.0153		-0.0087		-0.0101	
	(0.0409)		(0.0383)		(0.0389)		(0.0464)		(0.0448)	
High track, English	0.2735	***	0.0774	***	0.0781	***	0.0600	**	0.0583	**
	(0.0299)		(0.0255)		(0.0260)		(0.0268)		(0.0279)	
High track, Math	0.2866	***	0.0881	***	0.0959	***	0.0794	***	0.0900	***
	(0.0271)		(0.0238)		(0.0242)		(0.0256)		(0.0261)	
Parents contact school about grades	-0.1236	***	-0.0833	***	-0.0846	***	-0.0489	**	-0.0502	**
	(0.0205)		(0.0185)		(0.0189)		(0.0225)		(0.0232)	
Family rule about maintaining GPA	-0.1046	***	-0.0545	***	-0.0529	***	-0.0476	**	-0.0449	*
	(0.0212)		(0.0189)		(0.0193)		(0.0223)		(0.0231)	

Table 7: Assigned Grades, IV, Continued

	No controls	Eqn. (5)	Eqn. (6)	Eqn. (7)	Eqn. (8)
School: private	0.0349	-0.0444	-0.0346	0.0487	0.0384
	(0.0668)	(0.0640)	(0.0658)	(0.0561)	(0.0586)
School: student/teacher ratio	0.0117 ***	0.0141 ***	0.0139 ***	0.0114 ***	0.0111 ***
	(0.0040)	(0.0042)	(0.0041)	(0.0042)	(0.0042)
School: % free lunch	-0.0022 **	-0.0003	-0.0004	0.0013	0.0012
	(0.0009)	(0.0009)	(0.0009)	(0.0011)	(0.0011)
School: lowest teacher salary	-0.0063	-0.0048	-0.0044	-0.0006	-0.0008
	(0.0053)	(0.0054)	(0.0053)	(0.0048)	(0.0048)
College GPA				0.2161 ***	0.2145 ***
				(0.0174)	(0.0176)
Length of school day			0.0004		0.0002
			(0.0003)		(0.0004)
School has professional tutors			-0.0996 *		-0.1610
			(0.0572)		(0.0563)
School has peer tutors			-0.0138		-0.0036
			(0.0500)		(0.0524)
School has common prep periods for teachers			-0.0059		-0.0168
			(0.0394)		(0.0406)
School uses flex time for classes			-0.0527		-0.0226
			(0.0427)		(0.0428)
Math/Science Teacher certified in subject being taught			0.0478		0.0083
			(0.0543)		(0.0583)
Math/Science Teacher has degree in subject being taught			-0.0094		-0.0078
			(0.0233)		(0.0287)
Math/Science Teacher received no support for prof. development			0.0088		0.0220
			(0.0202)		(0.0244)
English/SS Teacher certified in subject being taught			-0.0198		-0.0345
			(0.0492)		(0.0583)
English/SS Teacher has degree in subject being taught			-0.0450 **		-0.0364
			(0.0202)		(0.0238)
English/SS Teacher received no support for prof. development			-0.0073		-0.0139
			(0.0207)		(0.0236)
Constant	2.6414 ***	0.7441 ***	0.5842 **	0.4729 **	0.4306
	(0.1715)	(0.1948)	(0.2364)	(0.2029)	(0.2614)
Mean of GPA	2.696	2.696	2.696	2.696	2.696
Standardized coefficient on Fragmentation	-0.011	-0.041	-0.034	-0.050	-0.046
Observations	3155	3040	2971	1669	1635
Adj. R^2	0.383	0.530	0.534	0.547	0.549